Forecasting Value at Risk: Evidence from Emerging Economies in Asia

Le Trung Thanh, Nguyen Thi Ngan, Hoang Trung Nghia

***Abstract*—In this paper, various Value-at-Risk techniques are applied to stock indices of 9 Asian emerging financial markets. The results from our selected models are then backtested by Unconditional Coverage, Independence, Joint Tests of Unconditional Coverage and Independence and Basel tests to ensure the quality of Value-at-Risk (VaR) estimates. The main conclusions are: (1) Time-varying volatility is the most important characteristic of stock returns when modelling VaR; (2) Financial data is not normally distributed, indicating that the normality assumption of VaR is not relevant; (3) Among VAR forecasting approaches, the backtesting based on in- and out-of-sample evaluations confirms its superiority in the class of GARCH models; Historical Simulation (HS), Filtered Historical Simulation (FHS), RiskMetrics and Monte Carlo were rejected because of its underestimation (for HS and RiskMetrics) or overestimation (for the FHS and Monte Carlo); (4) Models under student's t and skew student's t distribution are better in taking into account financial data's characters; and (5) Forecasting VaR for futures index is harder than for stock index. Moreover, results show that there is no evidence to recommend the use of GARCH (1,1) to estimate VaR for all markets. In practice, the HS and RiskMetrics are popularly used by banks for large portfolios, despite of its serious underestimations of actual losses. These findings would be helpful for financial managers, investors and regulators dealing with stock markets in Asian emerging economies.**

***Keywords*—Value at Risk, Forecast, Univariate GARCH, Emerging Financial Markets.**

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1 INTRODUCTION

AFTER the market failure in 2008, the demand for reliable quantitative measures in financial sector becomes greater than ever. Not only financial institutions but also investors are more cautious in their investment decisions, leading to an increased need for a more careful study of risk measurements in stock markets. Value at Risk (VaR) is currently the most popular and important tool for evaluating market risk – one of major threats to the global financial system. This tool was developed and popularized in the early 1990s by JPMorgan's scientists and mathematicians ("quants"). The VaR of portfolio is defined as the dollar loss that is expected to be exceeded (100 – X)% of the time over a fixed time interval. It is not only considered as an acceptable risk measure by corporations, asset managers but also the basis for the estimation of capital requirements as regulated by the Basel Committee on Banking Supervision (BCBS). However, the VaR has received a great deal of criticism after the outbreak of the 2008 global financial crisis owing to its inability in risk forecasting [29]. The BCBS, in its 2011 review of academic literature concerning risk measurement, submitted the incoherence of VaR as a risk measurement [12] and proposed expected shortfall (ES) to replace VaR [13] on the third Basel Accord. Nevertheless, none of these measures are without drawbacks. The principal shortcoming of ES is that it cannot be reliably backtested in the sense that forecasts of expected shortfall cannot be verified through comparison with historical observations, while VaR is easily backtested. In other words, expected shortfall is coherent but not "elicitable", while VaR is "elicitable" but not coherent. This makes VaR hold a regulatory advantage in measuring of risk relative to expected shortfall. VaR allows investors to make investment decisions by examining directions of market risk by comparing the two VaR's portfolios. The

Goldman Sachs' success in avoiding impacts of the 2007 subprime crisis is supposed to be owing to the using of VaR [49]. VaR, therefore, is still considered as the most important tool for evaluation of market risk. The European Commission (2014) has endorsed VaR, either as a regulatory standard or as the best practice. Many banks and financial institutions employ the concept of "value at risk" as a way to measure the risks of their portfolios.

There are multiple VaR methods used to estimate possible losses of a portfolio whose difference lies in calculating the density function of those losses. The first one is Historical Simulation (HS) which is non-parametric and based on historical returns. This method contains several critical disadvantages such as its inconsistency in allocation of past shocks while financial returns are highly influenced by time dependence which can cause volatility clustering. The error terms may reasonably be expected to be larger for some points or ranges of the data than for others (i.e. heteroskedasticity). Due to the presence of heteroskedasticity, regression coefficients for an OSL regression are no longer exact. To deal with this problem, a parametric approach has been introduced. In the pioneering paper, Engle introduced a method called the ARCH model [30]. This methodology was later developed by Bollerslev into GARCH (generalized ARCH) (1986) and Student's t-GARCH [16]. The former is proved to be better in capturing the inherent features of financial time series, namely fat tailed returns or volatility clustering while the latter shows that non-normalities can also be captured by the GARCH models with a flexible parametric error distribution. Despite the apparent success of these simple parameterizations, the initial GARCH model fails to capture an important feature of the data. French et al, Nelson, Grouard et al. and many others discovered this normal model does not address the leverage or asymmetric effect [35; 48; 37]. In particular, an unexpected drop in price (bad news) increases predictable volatility more than an unexpected increase in price (good news) of similar magnitude. The normal GARCH model over-predicts the amount of volatility following good news and under-predicts the amount of volatility following bad news. In addition, if large return shocks cause more volatility than a quadratic function allows, the standard GARCH model over-predicts volatility after a small return shock and under-predicts volatility after a large return shock. As a result, the GARCH model has been extended in various directions in order to overcome these characteristics of financial time series and to increase the flexibility of the original model. Among many extensions of GARCH, the most widely used is that of Bollerslev, namely GARCH(1,1) [16]. The survey by Bollerslev et al. and the study of Engle and Ng. also supported that the GARCH (1,1) is adequate for modeling many high frequency time series data [17; 31].

To assess the risk of financial transactions, estimates of asset return volatility is an important factor and therefore the center of attention of risk management techniques. Many VaR models for measuring market risk require the estimation or forecast of a volatility parameter. Since whoever could forecast volatility changes more precisely will be likely to better control the market risk, accurate measures and reliable forecasts of volatility are essential to numerous aspects of finance and economics. Nowadays, the GARCH model has become a widespread tool for measuring volatility in financial decisions concerning risk analysis, portfolio selection and derivative pricing. Besides, a new generation of VaR models which is based on the combination of GARCH modelling (parametric) and historical portfolio returns (non-parametric) is increasingly used in risk management. Barone-Adesi et al. and Barone-Adesi et al. propose FHS that can take into account changes in past and current volatilities of historical returns. Another increasingly popular model is Monte Carlo [9; 10; 11].

Our study investigates the relative performance of the different models in estimating and forecasting VaR which appear to yield reliable results for the US market as well as the emerging markets in Asia. Because of the different nature of emerging markets in relation to developed markets, one could expect different results. Moreover, the enormous growth of financial markets in the emerging countries in recent years has prompted the financial regulators and supervisory committees to look for well-justified methods to quantify risks. The aim of our study is to seek a conclusion on the performance of the methods for Asian emerging markets. The rest of this paper is organized as follows. Section 2 reviews the literature on this subject. In Section 3 we will explain concepts and theories of methodology employed in this paper. We present details of the data and empirical results obtained in Section 4 and conclusions are given in Section 5.

2 LITERATURE REVIEW

Because of its popularity, most empirical studies use VaR as risk measure. In order to calculate the VaR, one can choose HS, FHS, variance-covariance techniques and Monte Carlo simulation. Following the pioneering papers of Engle and Bollerslev, the use of VaR models is increasing [30; 16]. A vast financial literature has attempted to compare the accuracy of various models for producing out-of-sample volatility forecasts. However, those paper do not provide conclusive results. For example, when comparing VaR methodologies, the studies by Hendricks, Beder, among others [39; 15], concluded that the HS performed at least as well as more complex methodologies, namely the parametric approach (i.e. RiskMetrics, GARCH-normal, EGARCH, and Student's-t EGARCH) and the Monte Carlo simulation. By considering the three most common categories of VaR models (i.e. equally weighted moving average, exponentially weighted moving average, and HS), Hendricks found these approaches tend to produce risk estimates that do not differ greatly in average size and none appears to be superior [39]. Similar result in the study of Beder who employed variance-covariance, historical [15], and simulation VaRs suggests that different VaR methodologies are appropriate for different firms and depend on many factors. Study by Le and Nguyen employed parametric [55], non-parametric and semi-parametric to estimate VaR on 8 portfolios representative to emerging and developed markets. They found that all models are significant at 1% and 5% level and models with normal distribution assuptioms fail in predicting VaR. Ngo and Le used HS, GARCH and Cornish Fisher to estimate VaR and ES on 9 portfolios of Vietnam's listed banks [56]. Results show that the three models have equal performance. On the other hand, more recent papers have reported that the HS provides poor VaR estimates compared with other recently developed methodologies. In particular, Abad and Benito who compared several VaR methods: HS, Monte Carlo simulation, parametric methods and extreme value theory found that the parametric methods estimate VaR at least as well as other VaR methods that have been developed recently (e.g. the models based on extreme value theory), especially under an asymmetric specification for the conditional volatility and the Student's-t innovations [2; 3]. This result is robust with another sample and the confidence level of VaR [1]). Additional studies that find evidence in favor of parametric methods are Ñíguez, Sarma et al., Daníelsson, Akgiray, West and Cho, Pagan and Schwert, among others [38; 51; 26; 4; 58; 50]. Ñíguez provided an empirical study to assess the forecasting performance of a wide range of models in predicting volatility and VaR on Madrid Stock Exchange and find that FIAPARCH and Studen's-t distribution (or another suitable heavy-tailed distribution) should be considered when deciding the models to include in the pool [38]. Daníelsson investigated parametric approach (in particular the normal and student's-t GARCH) [26], HS and extreme value theory models and find evidence in favor of parametric methods. Akgiray compares GARCH, ARCH, exponentially weighted moving average and historical mean models in forecasting monthly US stock index volatility and finds GARCH model superior to the others [4]. The study of West and Cho using one-step-ahead forecasts of dollar exchange rate volatility provided a similar result concerning the apparent superiority of GARCH, although for longer horizons, the model behaves no better than its alternatives [58]. In another study, Pagan and Schwert compared GARCH, EGARCH, Markov switching regime and three non-parametric models in forecasting volatilities on monthly US stock returns. Results indicate that only EGARCH and GARCH models perform moderately while the other models produce very poor predictions [50].

When considering only parametric approach, the results of various studies carried out so far are not consistent. Drakes et al. modelled the return volatility of stocks traded in the Athens Stock Exchange using five classes of GARCH model with alternative probability density functions for error terms. They found that normal mixture asymmetric GARCH (NM-GARCH) with skewed student-t distribution performs better in modeling the volatility of stock returns, based on Kupiec's Test. A similar result concerning the apparent superiority of the asymmetric NN-GARCH is observed by Alexander and Lazar who applies 15 different GARCH models using alternative density function on three bilateral exchange rates, namely sterling-dollar, euro-dollar and yen-dollar [6]. In another study, Su concluded that EGARCH fits the sample data better than GARCH in modelling the volatility of China's stock returns [53]. This finding is further supported by Alberg et al. who applied various GARCH models to analyze the mean return and conditional variance on Tel Aviv Stock Exchange (TASE) [5]. Results indicate that asymmetric GARCH models with fat-tailed densities (especially the EGARCH with skewed Student-t distribution) are successful in forecasting TASE indices. By using various European stock market indices, Franses and Dijk found that non-linear GARCH models (i.e. QGARCH and the GJR) fail to outperform the standard GARCH in forecasting the weekly volatility [34]. On the other hand, the study of Brailsford and Faff (1996) on Australian monthly stock index shows that GJR and GARCH are slightly superior to various simpler filters in predicting volatility.

In addition, other studies also remarked sound results obtained from FHS. Barone-Adesi et al. (2000) backtested VaR generated by FHS model using three types of portfolios (LIFFE financial futures and options contracts traded on LIFFE, interest rate swaps, mixed portfolios consisting of LIFFE interest rate futures and options as well as plain vanilla swaps) invested over a period of two years. In each of their three backtests, they stored the risk measures of five different VaR horizons (1, 2, 3, 5 and 10 days) and four different probability levels (0.95, 0.98, 0.99 and 0.995). Their findings sustain the validity of FHS as a risk measurement model and diversification reduces risk effectively across the markets they study. Impressive gains in FHS compared with those of HS in Barone-Adesi and Giannopoulos' study (2001) confirm the superiority of FHS.

The above studies focused on stock indices, whereas few researches were conducted on futures indices. Market risk of stock index futures have been measured individually by Kaman (2009) (on Turkish Index Futures), Dechun et al. (2009) (on Shanghai Sehnzhen Stock 300 Index futures) [27], Cotter and Dowd (2006) (on FTSE100, S&P500, Hang Seng and Nikkei225 index futures) [25], Tang and Shieh (2006) (on S&P 500, Nasdaq 100, and Dow Jones stock index futures) [54], Huang and Lin (2004) (on Taiwan stock index futures) [41]. Not many empirical studies compare VaR on spot and futures indices. One of the few is that of Carchano et al. which compares the predictive performance of one-day-ahead VaR forecasts using normal and the CTS ARMA-GARCH models on S&P 500 [20], DAX 30, and Nikkei 225 spot and futures indices. Their findings show that in both markets the CTS performs better in forecasting one-day-ahead VaR than the model that assumes innovations followed the normal law. Köseoglu and Ünal analyzed the market risks of various future stock market indices and the market risks of their corresponding underlying stock markets (namely S&P500, DAX30, FTSE100, Nikkei225, ISE30) for the period between 2005 and 2011, using various approaches, e.g RiskMetrics, Delta Normal, Cornish Fisher modified, HS and extreme value theory [45]. They found that futures market risk is higher than underlying stock market risk for Nikkei 225 and S&P 500 while the opposite is true for FTSE, DAX and ISE 30. RiskMetrics approach is also so proved to produce the best forecasts to VaR measures.

In conclusion, above-mentioned studies prove that none is perfect method. Although a great deal of studies on risk measurement have been conducted, most of them mainly focus on developed countries and stock indices. Because of the different nature of emerging markets compared to developed markets, it is crucial to use alternative models to assess their performance in risk measurement of the stock returns and evaluate their forecasting in emerging markets. This paper aims to consider the out-of-sample forecasting performance of HS, FHS, GARCH family models and Monte Carlo in predicting futures markets and stock markets volatility in Asian emerging markets. The main differences between our study and previous literature are as follows: (1) In this comparison, a more exhaustive set of methods are employed, such as HS, FHS, Monte Carlo simulation and the parametric approach (in particular GARCH family models) in Asian emerging financial markets. (2) When conditional variance needs to be modelled, several models are applied (one of them is asymmetric GARCH under both a normal, a Student's-t distribution and Skew-Student's-t distribution of returns which allow leverage and fat-tail effect usually observed in financial returns); and (3) The VaR performance is analyzed after the periods of the financial crisis in

2008-2009.

3 METHODOLOGY

Measuring VaR can be classified into three general categories: Non-parametric (HS, FHS), parametric (variance-covariance techniques), and Monte Carlo simulation together with numerous variations for each approach. The essence of parametric approach is the distribution assumption, whereas nonparametric approach makes no assumption regarding distribution. A priori, it is not clear which method provides the best results. In this paper, we will compare three techniques applied to all stock market indices in emerging economies in Asia.

In non-parametric approach, the HS and the FHS are applied. In parametric approach, due to the great number of variations of GARCH that have that have been developed over the last 20 years, we restrict our study to a class of 8 GARCH models using different assumptions of distribution of innovations in addition to RiskMetrics. Consequently, we compare the actual values of those indices with the risk values predicted by the selected models which are known as backtesting. This method has been adopted by many financial institutions for gauging the quality and accuracy of their risk measurement. Realized day-to-day returns on the bank's portfolio are compared to the VaR of the bank's portfolio. By counting the number of times when the actual portfolio result was worse than the VaR, the performance of a model in predicting its true market risk exposure can be assessed. If this number corresponds to approximately percent of the back-tested trading days (i.e. prescribed left tail probability), the model is well specified or is rejected, otherwise.

The simplest model for VaR assessment is the HS. It is based on the assumption that history is repeating itself and all occurrences are independent and identically distributed (i.i.d.). The HS method accurately measures past returns but can be a poor estimator of future returns if the market has shifted. To overcome the shortcomings of traditional HS, the FHS incorporates conditional volatility models such as GARCH into the HS model. The FHS model allows time varying conditional moments of returns, volatility clustering and factors that can have an asymmetric effect on volatility. In addition, it is crucial in applications and avoids too simplistic assumptions about conditional normality distributions of returns. The empirical distribution of financial returns is simulated by considering different samples with the different lengths of window: k = 30 (1 month), k = 60 (2 months), k = 250 (1 year), 500 (2 years) daily observations for both methods to take the effect of different sizes of used training set into account.

The most commonly adopted VaR estimation method is the variance-covariance approach, which is based on a volatility forecast rather than a returns forecast. This paper employs AR(1) and GARCH(1,1) given their simplicity in estimation and theoretical properties of interest, such as tractable moments and stationary conditions. Furthermore, the distributions are often asymmetric and fat-tailed, whereas the normal assumption is found to be inadequate for sample fitting and forecasting not long after its inception. In addition, many studies show the fat tails of the distribution can best be modeled by means of the t-distribution. As a result, student's t-distribution and skew student's t-distribution are also adopted with additional shape parameters and perform better than a model with Gaussianity, particularly for more extreme (1% or less) VaR thresholds. For parametric approach, we apply nine VaR measures for each index, namely: EWMA, GARCH, EGARCH, GJR-GARCH, IGARCH, TGARCH, AVGARCH, NGARCH, NAGARCH, and ALLGARCH. Within each model, we have considered three types of distributions: Normal, Student's t and Skew-Student's t-distribution.

Another popular method is the Monte Carlo simulation. This is a flexible approach as it allows users to modify individual risk factors, thereby providing a more comprehensive picture of potential risks embedded in the down-side tail of the distribution by generating large number of scenarios. In finance, it is a reasonable assumption that asset prices are mostly unpredictable and follow a special type of stochastic process known as geometric Brownian motion [52; 22]. The following equation describe the geometric Brownian motion:

$$S_{t+\Delta t}=S_t e^{k\Delta t+\sigma\varepsilon_t \sqrt{\Delta t}} \qquad (1)$$

where S_t is the stock price at time t, e is the natural logarithm, Δt is the time increment (expressed as portion of a year in terms of trading days), $k=\mu-\sigma^2/2$ is the expected return and ε_t is the randomness at time t (random number generated from a standard normal probability distribution) introduced to randomise the change in stock price.

Simulations are computationally intensive and thus much time-consuming and requiring more knowledge and experience of the users than both the parametric methodology and HS. In addition, number of market risk factors keep increasing and more complex, while a simulation is only as good as the probability distribution for the inputs that are fed into it. Nevertheless, Monte Carlo simulation can be a valuable tool for forecasting an unknown future in financial sector.

The VaR calculated with the aforementioned volatility model should always be accompanied by validation, i.e. checking whether it is adequate or how well it predicts risks. This is the key part of the internal model's approach to market risk management in order to evaluate alternative models, especially when comparing methods. In backtesting, the historical VaR forecasts and their associated asset returns are used to check if actual losses are in line with expected losses. In our paper, Unconditional Coverage Tests, Independence Tests and Joint Tests of Unconditional Coverage and Independence are applied to compare the accuracy, independence and the joint performance of each VaR estimation method.

4 DATA AND EMPIRICAL FINDINGS

4.1 Data

Data employed in this paper is daily adjusted closing indexes of 8 emerging markets in Asia, namely Shanghai Composite Index SSE (China), S&P BSE SENSEX (India), Jakarta Composite Index JKSE (Indonesia), Kospi Index KS11 (Korea), KLSE (Malaysia), PSEi-Index PSEI.PS (the Philippines), TSEC weighted index TW (Taiwan), SET Index (Thailand) and VN-Index (Vietnam). For index futures, only four markets, which are Taiwan (FTWII), Korea (FKS11), Malaysia (FKLCI), India (FBSESN)) are employed to consider whether stock index futures are riskier than their underlying assets due to data unavailability of the other markets. The studied period is from January 2000 to December 2014. All data was obtained from Yahoo Finance and DataStream.

The total sample of stock returns is divided into estimation and evaluation sub-samples. The out-of-sample evaluation sample contains 900 last observations in the total sample for each index. The indices are transformed to daily rate of returns, which are defined as the natural logarithmic returns in two consecutive trading days:

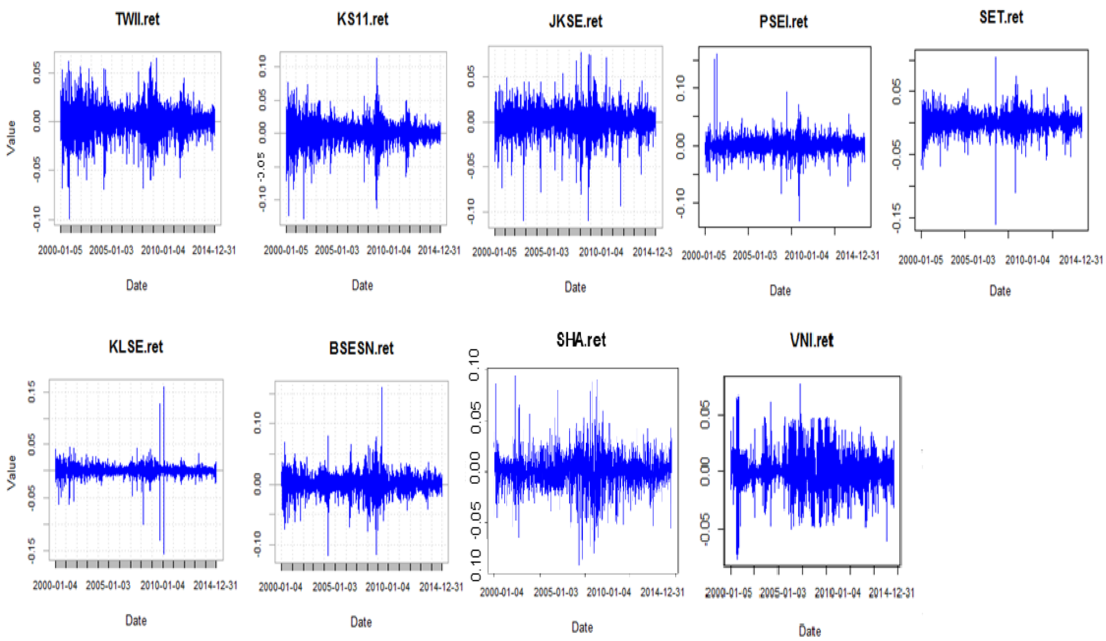
$$r_t=\ln(p_t)-\ln(p_{t-1})=\ln(p_t/p_{t-1})$$

where r_t is the daily log return, p_t and p_{t-1} are the daily adjusted closing price of each stock indices at time t and t-1.

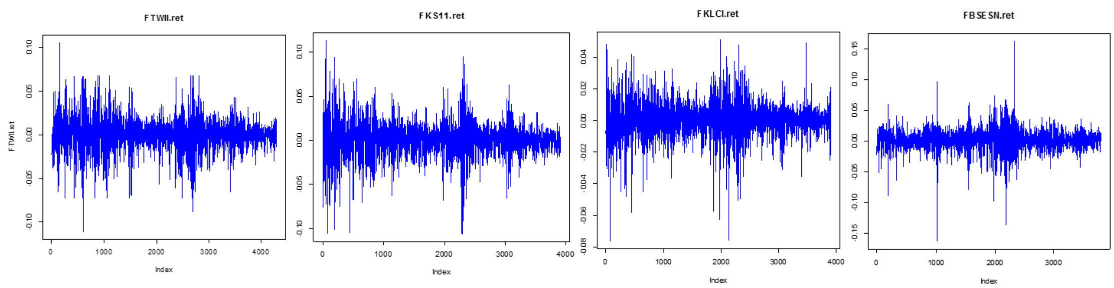
The plots for the daily log returns fluctuate around a zero mean. Each of all series appears to show signs of ARCH effects in which the amplitude of the returns varies over time (see Figure 1). The p-value of ARCH Test shown in the last row are all zero, resoundingly rejecting the "no ARCH" hypothesis (See Table 1). By observing the time series data set of returns, it can be seen that there exists heteroskedasticity. However, we cannot determine whether this is enough to warrant consideration.

Table 1 shows that the average daily return are positive (except for TWII about 0%) but negligibly small compared with the sample standard deviation. The daily standard deviation of stock indices of the Korean and Vietnamese markets are the highest (0.0164), whereas that of the Malaysian is the lowest (0.0098). For index futures, Korean market also has the highest standard deviation (0.0175) and Malaysian market has the lowest standard deviation (0.0106). Furthermore, stock index futures are riskier than their underlying assets as evidenced by their higher standard deviation compared with stock indices. The reason is that futures market risk is related not only to changes in the underlying assets but also many other speculative trading activities.

The returns series are skewed (either negatively or positively) and the large returns (either positive or negative) lead to a large degree of kurtosis. Both the assets show evidence of fat tails (leptokurtic), since the kurtosis exceeds 3 (the normal value), implying that the distribution of these returns has a much thicker tail than the normal distribution. As we know, skewness is a measure of symmetry, which is equal to zero for normal distribution. The skewnesses of all markets (except for PSEI.PS) are also negative, which means that the distribution has an asymmetric tail extending out to the left and is referred to as "skewed to the left". This leads the standard deviation of all markets which presents the "risk" is underestimated when kurtosis is higher and skewness is negative. The Ljung-Box (LB) Q statistics for daily stock returns of both assets are highly significant at five-percent level indicate the presence of serial correlations. Furthermore, the Ljung-Box Q statistics for squared returns are much higher than that of raw returns indicate the time-varying volatility. Furthermore, the presence of serial correlations and time-varying volatility make the traditional OLS regression inefficient. These results indicate that GARCH model would be a more suitable model than the tradition OSL regression models in estimating the "true risk".



(a) The daily returns of stock indices



b) The daily returns of stock index futures

Figure 1. The daily returns of and stock indices and stock index futures

4.2 *Empirical Findings*

The results of backtesting at VaR 99% and VaR 95% for all indices are presented in Table 2. For each index, the rejected models are hightlighted in yellow. Graphical representations are not reported here because of limited space yet available upon request.

It can be observed that models provide relatively similar results for all indices. As presented in Table 2, FHS appears to be superior to HS for all indices since results produced by HS are relatively far away from the threshold in most of the cases. The backtest results of HS is rather disappointing as most failure rates considerably exceed the respective left tail probabilities. HS models also yield the poorest outcomes as evidenced by the number of exceptions being distant from the expected ones. Not surprisingly, three backtests reject almost all of these models for all left tail probabilities. In particular, HS models differ primarily in the span of time they include. The results also show that the longer the look-back period is, the lower exceptions the model yields. This can be explained that in finance and banking sector, the more derivatives are developed, the more dangerous the market is. The assumption of the future repeats the past will lead to inaccurate result.

If failure rates only are considered, FHS appears to be the best method. However, Figure 2 which illustrates the results of backtesting on daily returns and VaR exceedences of TWII using FHS method provides an opposite conclusion. Estimated lines from FHS method indicates that the estimated VaR is not responsive to historical data. This is likely due to the fact that these models overestimate VaR, resulting in useless VaR measure and low predicting power. Monte Carlo simulation also yields similar results.

In variance-covariance approach, RiskMetrics is the worst model as it yields the highest failure rates. It is noteworthy that RiskMetrics which causes VaR underestimation in reality is used as one of the most popular models by financial institutions. The underperformance of HS and RiskMetrics can be attributed to their rigid structure of adjustment to the volatility process. Accordingly, their responding adjustment is not fast enough to capture the vibrant market dynamics.

Backtesting results indicate that models with student's and skew student's distribution outperform the normal distribution. Possible reason is they cover all stock's characteristics (namely fat tail and skewness) (see Bollerslev and Heracleous) [16]. As the recommendation of Hendricks, the t-distribution is significant to capture outcomes in the tail of the distribution because extreme outcomes occur more often under t-distributions than under the normal distribution [39]. Study by Le and Nguyen also finds that models with normal distribution assumption failed to predict VaR at 1% significant level [55]. Another interesting finding is that GARCH models are rejected because of the lower than expected failure rate ratios while HS and RiskMetrics yield the opposite result with high failure rate ratios for all markets. This suggests that GARCH models overestimate VaR while the HS and Risk Metrics approach underestimate VaR in some cases. The underestimating feature of VaR has been proved in a plenty of studies in the past 2008 crisis.

It is worth noting that almost all of GARCH models are rejected at VaR 1% for the Vietnamese market. Historically, the choice of confidence interval was dependent on the bank's risk appetite and on a specific target the bank had for its rating, yet regulators require back testing only "on the 99th percentile". Mehta et al., show that the range of confidence intervals employed lies between 99.91% and 99.99% [47].

The research also shows that banks with significant capital markets activity tend to use 99.98%. Therefore, the fact that almost all models of GARCH family are rejected indicates that the Vietnamese markets are riskier and harder to estimate than others. It is likely because they are immature and prone to be distorted by multiple factors compared with other markets. This also explains why HS seems to be slightly more effective than others when being applied for Vietnam.

Findings also show that futures market forecast is less accurate than underlying stock market for almost all markets (except for KS11 and FKLCI at VaR 5%). As we know that futures markets tend to be influenced not only by changes in the underlying assets but also speculative trades. This feature is supposed to cause difficulties in its VaR forecasting. In fact, forecasting VaR using these models proves to be less accurate for the stock index futures than for the stock market, which means investors who take part in futures markets face more risk than those in stock markets. In addition, HS methods were less accurate for stock indices. However, the results are more accurate for index futures. Previous studies on developed markets have also shown the low accuracy of HS compared with other approaches in forecasting VaR. This is likely due to the fact that future markets in developed countries are more dynamic and mature than in the emerging countries. As a result, investors in emerging markets mainly rely on price history to make investment decisions. HS approach is slightly superior for index futures.

Finally, the study confirms that there is no evidence to propose the best GARCH (1,1) model for estimating VaR in all markets. Each market with specific conditions need specialized models for the estimation of volatility in reality.

5 CONCLUSIONS

In the paper we attempted to examine how well VaR models perform in Asian emerging markets.

The first conclusion is that our data are not normally distributed, indicating that the normality assumption of VaR is not reliable as discussed in the methodology part.

For each model, student's t distribution and skew student's t distribution are considered in order to model financial returns' characters. The performances of the volatility models were subsequently measured out-of-sample using VaR. Furthermore, our empirical results are in line with what we expected to find. We employed the Unconditional Coverage, Independence, Joint Tests of Unconditional Coverage and Independence to backtest these results to ensure the quality of our VaR estimates. In estimating VaR, it seems that for all indices, GARCH family models are clearly superior to HS, FHS, RiskMetrics and Monte Carlo simulation since their results are relatively far away from the threshold in most of the cases. This is not surprising because – as argued in lot of studies – GARCH family models should provide an accurate estimate of VaR. The results also indicate that models under student's t and skew student's t distribution are better in taking into account financial data's characters. The noticeable finding is that there is no evidence to choose the best model in the GARCH (1,1) family which can be used for estimating VaR in all markets. Furthermore, the reason that models in the GARCH family are rejected is the overestimated VaR which reduces the effectiveness of using inputs. This paper also shows that forecasting VaR for stock index futures is harder than for stock index. Those findings would be helpful for financial managers, investors and regulators dealing with stock markets in Asian emerging economies. Further extension of this work can be a research of alternative methods to estimate Value at Risk, e.g. the Conditional Autoregressive Value at Risk (CAVaR), an Incremental VaR (IVaR), Marginal VaR, Conditional VaR and Probability of Shortfall.

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Dự báo giá trị chịu rủi ro (VaR): Nghiên cứu từ các quốc gia Châu Á mới nổi

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***Tóm tắt*—Trong bài nghiên cứu này, chúng tôi áp dụng nhiều kỹ thuật tính giá trị chịu rủi ro (VaR) của 9 chỉ số chứng khoán của các quốc gia Châu Á mới nổi. Kết quả từ các mô hình sau đó được kiểm tra lùi bằng các phương pháp như Unconditional Coverage, Independence, Joint Tests of Unconditional Coverage và Independence, Basel để đảm bảo chất lượng của các ước tính VaR. Các kết quả chính của nghiên cứu là: (1) Biến động thay đổi theo thời gian là đặc điểm quan trọng nhất của tỷ suất sinh lời chứng khoán khi mô hình hóa VaR; (2) Các số liệu tài chính không có phân phối chuẩn, hàm ý rằng giả định phân phối chuẩn của VaR là không phù hợp; (2) Trong số các phương pháp dự báo VaR, kết quả kiểm tra lùi trong và ngoài mẫu cho thấy các mô hình GARCH có độ chính xác vượt trội; Phương pháp Historical Simulation (HS), Filtered Historical Simulation (FHS), RiskMetrics và Monte Carlo bị bác bỏ do dự báo quá cao (HS var RiskMetrics) hoặc dự báo quá thấp (FHS và Monte Carlo); (4) Các mô hình có phân phối student's t và student's t lệch tích hợp các đặc điểm của số liệu tài chính tốt hơn; và (5) Dự báo VaR đối với các chỉ số tương lai khó hơn dự báo chỉ số chứng khoán. Ngoài ra, kết quả cũng cho thấy không có cơ sở để khuyến nghị dùng GARCH(1,1) để ước tính VaR cho tất cả các thị trường. Trên thực tế, HS và RiskMetrics được các ngân hàng sử dụng phổ biến đối với các danh mục lớn mặc dù các phương pháp này dự báo tổn thất thực sự quá thấp. Những kết luận này sẽ giúp các nhà quản lý, đầu tư tài chính và cơ quan lập pháp quản lý tốt hơn thị trường chứng khoán của các quốc gia Châu Á mới nổi.**

Từ khóa—VAR, dự báo, GARCH đơn biến, các thị trường tài chính mới nổi

APPENDIX

DESCRIPTIVE STATISTICS OF DATA

	TWII	KS11	JKSE	PSEI.PS	SET	KLSE	BSESN	SHA	VNI	FTWII	FKS11	FKLCI	FBSESN
Observations	3707	3706	3631	3682	3671	3698	3710	3912	3421	3912	3912	3912	3797
Minimum	-0.0994	-0.1280	-0.1095	-0.1309	-0.1606	-0.1557	-0.1181	-0.0926	-0.0766	-0.1108	-0.1054	-0.0759	-0.1626
Maximum	0.0652	0.1128	0.0762	0.1618	0.1058	0.1602	0.1599	0.0940	0.0774	0.1057	0.1131	0.0510	0.1619
Mean	0.0000	0.0002	0.0006	0.0003	0.0003	0.0002	0.0004	0.0002	0.0005	0.0000	0.0002	0.0002	0.0005
Median	0.0004	0.0008	0.0012	0.0004	0.0006	0.0004	0.0011	0.0000	0.0002	0.0000	0.0000	0.0000	0.0001
Std. Dev.	0.0146	0.0164	0.0144	0.0135	0.0142	0.0098	0.0158	0.0152	0.0164	0.0164	0.0175	0.0106	0.0158
Variance	0.0002	0.0003	0.0002	0.0002	0.0002	0.0001	0.0003	0.0002	0.0003	0.0003	0.0003	0.0001	0.0002
Kurtosis	5.9749	8.7073	6.1732	15.0296	9.0349	57.7963	6.7603	4.9059	2.5798	4.2683	4.6913	4.7160	10.3493
Skewness	-0.2359	-0.5617	-0.6850	0.3177	-0.7213	-0.5187	-0.1876	-0.1004	-0.2056	-0.1842	-0.3483	-0.4670	-0.4565
LB Qstatistics													
Daily Returns													
LB (12)	37.44	16.3	54.94	85.2	41.21	7.657	47.45	26.27	451.1	48.15	16.76	21.4	45.8
	(0.000)	(0.177)	(0.000)	(0.000)	(0.000)	(0.811)	(0.000)	(0.009)	(0.000)	(0.000)	0.0158	0.0448	(0.000)
LB (24)	62.48	38.94	87.31	109.6	65.88	28.87	81.53	62.52	528.9	75.67	48.03	41.29	68.58
	(0.000)	(0.027)	(0.000)	(0.000)	(0.000)	(0.225)	(0.000)	(0.000)	(0.000)	(0.000)	0.0025	0.0154	(0.000)
Squared Daily Returns													
LB (12)	1244	1258	847	168.8	680.4	759.4	1108	572.2	7692	1380	1524	909.8	834.4
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LB (24)	2094	1769	1130	202.9	789	759.7	1556	917.4	11960	2285	2382	1245	1049
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ArchTest (12)	457.8	503	391.5	120	426.3	1022	437.7	272.8	1493	506.1	546.9	390.7	396.1
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: Descriptive statistics calculated for the whole period which goes from 01/01/2000 to 31/12/2014.

THE RESULT OF BACKTESTING AT VAR

	TWII		KS11		JKSE		PESI		SET		KLSE		BSESN		SHA		VNI		FTWII		FKS11		FKLCI		FBSESN	
	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%
HS30	**3.7%**	**7.4%**	**4.2%**	**6.6%**	**3.6%**	**7.4%**	**4.7%**	**6.7%**	**4.3%**	**7.6%**	**3.6%**	**6.8%**	**3.6%**	6.3%	**3.6%**	**6.7%**	**3.7%**	**7.1%**	**3.7%**	**6.7%**	**3.9%**	**7.6%**	**3.2%**	**7.7%**	**4.1%**	**7.1%**
HS60	**2.0%**	**4.7%**	**2.1%**	**5.3%**	**2.3%**	5.6%	**2.3%**	**5.9%**	**2.4%**	5.9%	**2.1%**	**5.0%**	1.7%	4.9%	1.7%	4.4%	**2.6%**	4.9%	1.7%	4.4%	**2.0%**	4.9%	1.6%	5.6%	1.7%	5.1%
HS250	0.8%	**5.2%**	**1.2%**	**5.0%**	1.4%	**5.7%**	**1.4%**	**4.9%**	1.7%	**5.3%**	**1.3%**	**4.9%**	1.3%	5.3%	1.0%	4.3%	1.2%	4.7%	0.9%	**5.1%**	**1.4%**	**4.4%**	1.6%	5.6%	1.3%	4.9%
HS500	0.8%	**4.1%**	**0.8%**	**4.2%**	0.6%	**4.2%**	**1.1%**	**4.8%**	0.8%	4.6%	1.1%	**4.8%**	0.8%	4.2%	0.7%	4.0%	0.9%	3.9%	0.6%	**4.3%**	**1.2%**	**4.0%**	0.9%	5.2%	0.7%	**3.4%**
FHS30	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
FHS60	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
FHS250	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
FHS500	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
RM-norm	**2.1%**	**5.8%**	**3.0%**	**7.3%**	**2.4%**	**7.1%**	**2.2%**	**7.0%**	**3.8%**	**7.0%**	**2.7%**	**4.7%**	**1.8%**	6.2%	**2.0%**	6.1%	**2.4%**	6.1%	**2.4%**	5.9%	**3.7%**	**7.9%**	**2.9%**	**7.4%**	**1.8%**	6.3%
RM-std	1.7%	**7.1%**	**2.4%**	**8.0%**	1.7%	**8.0%**	**1.6%**	**7.1%**	**2.7%**	**7.1%**	**2.2%**	**8.7%**	1.6%	**7.0%**	1.3%	**6.8%**	**2.3%**	**6.6%**	**2.1%**	**6.8%**	**3.0%**	**8.3%**	**2.3%**	**8.0%**	1.0%	**7.2%**
RM-sstd	1.2%	**6.2%**	1.0%	**6.9%**	1.6%	**7.6%**	**1.4%**	**7.0%**	**2.4%**	**7.1%**	**1.9%**	**8.4%**	1.2%	6.2%	1.2%	6.3%	**2.4%**	**6.7%**	**2.0%**	**6.6%**	1.7%	**7.8%**	**2.3%**	**7.9%**	0.9%	6.4%
Garch-norm	1.3%	4.4%	1.0%	5.4%	1.3%	4.9%	1.2%	**3.8%**	1.1%	3.9%	**2.0%**	**4.1%**	1.0%	4.7%	1.6%	4.3%	**2.0%**	5.1%	**1.8%**	4.6%	**1.8%**	6.0%	**1.9%**	4.9%	0.7%	4.6%
Garch-std	1.0%	5.4%	0.7%	**6.0%**	1.0%	5.4%	1.1%	4.1%	0.9%	5.4%	0.9%	4.3%	0.7%	5.0%	1.0%	5.7%	**1.9%**	5.9%	1.6%	5.6%	0.8%	**6.7%**	1.7%	6.2%	0.7%	4.9%
Garch-sstd	0.9%	4.7%	0.6%	**5.1%**	0.9%	4.9%	0.8%	4.0%	0.8%	5.0%	0.8%	3.9%	0.4%	4.4%	0.9%	4.9%	**2.0%**	5.7%	1.2%	5.2%	0.4%	6.0%	1.7%	5.6%	0.4%	4.3%
eGarch-norm	1.1%	4.3%	0.8%	4.4%	1.6%	4.3%	1.2%	4.0%	1.2%	3.9%	1.0%	**2.7%**	0.8%	3.8%	1.6%	4.7%	**1.9%**	4.7%	1.6%	4.1%	1.2%	5.2%	**1.9%**	4.7%	0.6%	3.9%
eGarch-std	1.0%	4.7%	0.4%	4.7%	0.9%	5.0%	1.0%	4.2%	1.1%	5.6%	1.0%	4.6%	0.7%	4.0%	1.0%	5.3%	1.4%	4.9%	1.3%	4.9%	0.7%	5.4%	1.4%	5.4%	0.4%	4.3%
eGarch-sstd	0.9%	4.2%	**0.2%**	4.1%	0.9%	4.2%	0.8%	4.1%	1.0%	5.0%	0.8%	4.0%	**0.3%**	**3.4%**	0.8%	4.9%	1.6%	4.9%	1.2%	4.7%	**0.3%**	4.9%	1.4%	5.2%	**0.3%**	4.2%
gjrGarch-norm	1.0%	4.1%	0.7%	4.7%	1.2%	4.3%	1.0%	3.8%	1.1%	**3.6%**	**2.2%**	3.9%	1.0%	3.9%	1.4%	4.4%	**2.0%**	5.1%	**1.8%**	3.8%	0.8%	5.4%	**1.8%**	4.7%	0.7%	4.0%
gjrGarch-std	1.0%	5.0%	0.4%	4.7%	0.9%	4.8%	0.8%	4.0%	0.9%	5.1%	0.8%	4.2%	0.6%	3.9%	1.0%	5.2%	**1.9%**	5.9%	1.4%	4.9%	0.6%	5.9%	1.4%	5.2%	**0.3%**	4.1%
gjrGarch-sstd	0.8%	4.3%	0.4%	4.2%	0.8%	4.3%	0.8%	3.9%	0.8%	4.8%	0.8%	3.8%	**0.3%**	3.7%	0.7%	4.7%	**2.0%**	5.8%	1.3%	4.4%	**0.3%**	5.1%	1.4%	5.0%	**0.3%**	4.0%
iGarch-norm	1.4%	4.8%	1.1%	6.0%	1.3%	4.9%	1.1%	**3.8%**	1.0%	4.3%	**2.2%**	**4.2%**	1.0%	4.8%	1.7%	4.9%	**2.0%**	5.1%	**1.9%**	4.4%	**2.3%**	6.1%	**2.1%**	5.0%	0.7%	4.7%
iGarch-std	1.0%	5.6%	0.7%	**6.4%**	0.9%	5.4%	0.8%	4.0%	1.1%	5.6%	0.9%	4.8%	0.6%	5.1%	1.0%	5.7%	**1.9%**	5.9%	1.6%	5.6%	0.8%	**6.7%**	1.7%	6.2%	0.4%	4.9%
iGarch-sstd	0.9%	4.9%	0.6%	5.4%	0.8%	4.9%	0.6%	**3.6%**	0.9%	5.4%	0.8%	4.0%	0.4%	4.6%	0.8%	4.9%	**2.0%**	5.7%	1.2%	5.2%	0.4%	6.0%	1.7%	**5.6%**	0.4%	4.6%
TGarch-norm	1.0%	4.1%	0.7%	4.2%	1.6%	4.3%	1.2%	4.0%	1.1%	3.7%	1.1%	**3.1%**	0.9%	3.8%	1.6%	4.6%	**2.2%**	4.9%	1.6%	3.9%	1.1%	5.1%	**1.8%**	4.6%	0.7%	3.8%
TGarch-std	1.0%	4.8%	**0.3%**	4.6%	1.0%	4.7%	1.0%	4.3%	1.1%	5.4%	0.9%	4.7%	0.6%	3.9%	1.0%	5.4%	1.4%	5.2%	1.2%	4.9%	0.6%	5.3%	1.4%	5.1%	**0.2%**	4.0%
TGarch-sstd	0.9%	4.0%	**0.2%**	**3.4%**	0.9%	4.1%	0.9%	4.2%	1.0%	5.0%	0.9%	4.6%	**0.3%**	**3.3%**	0.8%	4.8%	**1.8%**	5.2%	1.2%	4.3%	**0.3%**	4.7%	1.4%	5.1%	**0.2%**	4.0%
AVGarch-norm	1.0%	4.3%	0.7%	**3.7%**	1.6%	4.1%	1.1%	**4.0%**	1.4%	4.4%	**2.1%**	**4.2%**	0.8%	**3.6%**	1.6%	4.6%	**2.0%**	4.8%	1.6%	3.9%	0.9%	4.6%	**1.8%**	4.6%	0.8%	3.7%
AVGarch-std	1.0%	4.1%	**0.3%**	**3.6%**	1.1%	4.8%	0.9%	4.0%	0.9%	5.1%	0.9%	4.7%	0.6%	3.7%	0.9%	5.4%	1.4%	5.2%	1.3%	5.1%	**0.3%**	4.6%	1.4%	5.2%	**0.2%**	4.1%
AVGarch-sstd	1.0%	4.0%	**0.2%**	**2.9%**	0.9%	4.2%	1.0%	3.8%	0.9%	4.9%	0.9%	4.6%	0.4%	**3.3%**	0.8%	4.9%	**1.8%**	5.1%	1.2%	4.3%	**0.2%**	4.2%	1.4%	5.0%	**0.3%**	3.7%
NGarch-norm	1.4%	4.4%	0.8%	5.3%	1.3%	4.7%	1.2%	3.8%	–	–	–	–	1.1%	4.9%	1.6%	4.7%	**2.1%**	4.9%	**1.8%**	4.4%	**1.9%**	6.0%	–	–	0.8%	4.4%
NGarch-std	–	–	–	–	0.9%	5.6%	–	–	1.2%	5.9%	–	–	0.7%	5.1%	1.0%	5.6%	1.6%	5.2%	1.6%	5.6%	–	–	–	–	0.7%	4.9%
NGarch-sstd	–	–	–	–	–	–	–	–	0.9%	5.7%	–	–	0.4%	4.7%	0.9%	5.1%	1.7%	5.1%	1.3%	5.0%	–	–	–	–	0.4%	4.3%
NAGarch-norm	1.0%	4.0%	0.6%	4.1%	1.3%	4.1%	1.1%	3.8%	1.1%	**3.2%**	**2.1%**	**3.9%**	0.9%	**3.4%**	1.4%	4.7%	**2.0%**	5.1%	1.4%	**3.6%**	0.8%	5.1%	**2.1%**	4.6%	0.9%	3.7%
NAGarch-std	0.9%	4.4%	**0.3%**	4.7%	1.1%	4.3%	0.8%	4.1%	0.9%	5.3%	0.8%	4.1%	0.7%	3.7%	1.0%	5.1%	**1.9%**	5.8%	1.4%	4.8%	0.4%	5.2%	1.4%	5.1%	**0.3%**	3.8%
NAGarch-sstd	0.8%	**3.9%**	**0.2%**	**3.2%**	0.9%	4.0%	0.8%	4.0%	0.9%	5.0%	0.8%	3.9%	0.6%	**3.0%**	0.8%	4.9%	**2.0%**	5.9%	1.2%	4.2%	**0.3%**	4.6%	1.4%	5.0%	**0.2%**	**3.3%**
Monte Carlo	**0.2%**	**1.7%**	**0.1%**	**1.0%**	0.4%	**1.9%**	0.6%	**2.1%**	0.4%	**1.9%**	**2.0%**	4.7%	**0.1%**	**1.3%**	0.4%	**1.9%**	**0.1%**	**1.1%**	**0.2%**	**1.3%**	0.6%	**1.7%**	0.7%	**1.4%**	**0.3%**	**0.7%**

Note: RM is RiskMetrics, norm is normal distribution, std is student's t distribution, sstd is skew student's t distribution. The yellow cells indicate that the null hypothesis that the VaR estimate is accurate is rejected by any test. Results of unconditional coverage test, serial independence, conditional coverage will be available upon request.

BACKTESTING - DAILY RETURNS AND VAR EXCEEDENCES OF TWII USING FHS METHOD